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QUANTITATIVE METHODS FOR LONG-RANGE ENVIRONMENTAL FORECASTING: LONG-RANGE EUROPEAN PROJECTIONS

VOLUME III
RESEARCH GUIDE

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PREFACE

This Research Guide complements a two-volume document entitled A General Handbook for Long-Range Environmental Forecasting published by CACI, Inc. in February 1973. Volume I of the Handbook discusses important techniques that are applicable to long-range environmental forecasting and presents a bibliography of long-range forecasting studies while Volume II describes data files that may be of use to long-range forecasters in the national security community.

The Research Guide is designed to be used in conjunction with the Handbook. The Guide itself does not describe forecasting techniques but demonstrates how the techniques discussed in the Handbook can be applied to long-range forecasting. The Guide is divided into four chapters. Chapter 1 describes the building of a model; Chapter 2 discusses the data collection phase of the forecasting effort; Chapter 3 describes parameter estimation or the manner in which variables are related to one another; and Chapter 4 presents a hypothetical long-range forecast that uses the forecasting procedures described in the first three chapters of the Guide.

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CHAPTER 1: THE CONCEPTUAL MODEL

BUILDING THE MODEL

A "conceptual model" is a representation of the interrelationships among the components of a system. It may be based on hunches, intuition, experience, superstition, "book learning" or, more commonly, all of these. In forecasting, anyone who attempts to predict a future event or explain a historical one has a conceptual model that permits him to filter out the unimportant and link what is important in comprehensible ways. Thus any forecast requires a conceptual model, and a systematic forecast requires that a conceptual model be developed systematically.

The development of such a conceptual model has two distinct phases--isolating the important factors and identifying the causal relationships among them. Factors are those measurable aspects of a situation that either change (variables) or remain constant (parameters), and are the focus of the investigation. Relationships link changes in some factors with changes in others. The <u>modus operandi</u> of any forecasting methodology is to establish these relationships.

The most systematic forms of forecasting use statistical methods to determine the most appropriate "functional form" of a relationship among factors by analyzing how well such forms explain or predict past history as represented by data. Once the best relationship is determined, it is applied to current data on the assumption that the best relationship for explaining the past will be most appropriate for

predicting the future. The first step in the process, however, is to identify the factors in the model.

Factors

Factors consist of parameters and variables. Variables are factors that change whereas parameters are factors that remain constant. An example of a parameter is the number of permanent members in the United Nations Security Council. A variable, on the other hand, is a quantity that changes such as the number of accusations the Indian Government directs at the Pakistani Government each month.

The impact of time on the various factors of a system is crucial when building a conceptual forecasting model. In the very long run most factors tend to be variables, while in the very short run most factors tend to be parameters. An example may help illustrate the importance of the time frame in differentiating parameters from variables. Consider a forecast of Yugoslavia's alignment with the United States over the next 6 months. In this short-run forecast many factors are parameters. We can assume that Yugoslavia will maintain its Marxist form of government and that Tito will continue to be the head of state and hence influence Yugoslavia's alignment posture. On the basis of these parameters, a forecast of Yugoslavia's alignment can be generated. If the time frame of the forecast is extended to 10 years, however, many of the factors will become variables. It is questionable, for example, whether Tito will still be in public service in 10 years, let alone chief of state. Furthermore, over the next 10 years, Yugoslavia might adopt a more or a less authoritarian form of Marxist rule.

<u>Variables.</u> Within the context of a particular model, variables are

either exogenous or endogenous. The values of exogenous variables are determined outside the system considered, that is, they are taken as given. Thus the American GNP may be exogenous to the level of conflict between the United States and Canada. This variable may partially determine changes in the level of conflict; but such conflict is not likely to determine changes in the American GNP.

Exogenous variables are of two types--nonmanipulables and manipulables. Nonmanipulable exogenous variables are variables that are not affected by man-made decisions such as time, earthquake activity, and to a lesser degree weather and culture. Manipulable exogenous variables, on the other hand, can be consciously changed such as the level of foreign aid the United States gives to a less developed country. Thus, if a developing country becomes more aligned with the United States when given more aid, the United States can partially determine the alignment of that country by furnishing it with a certain level of aid. Foreign aid, in this instance, is a manipulable exogenous variable.

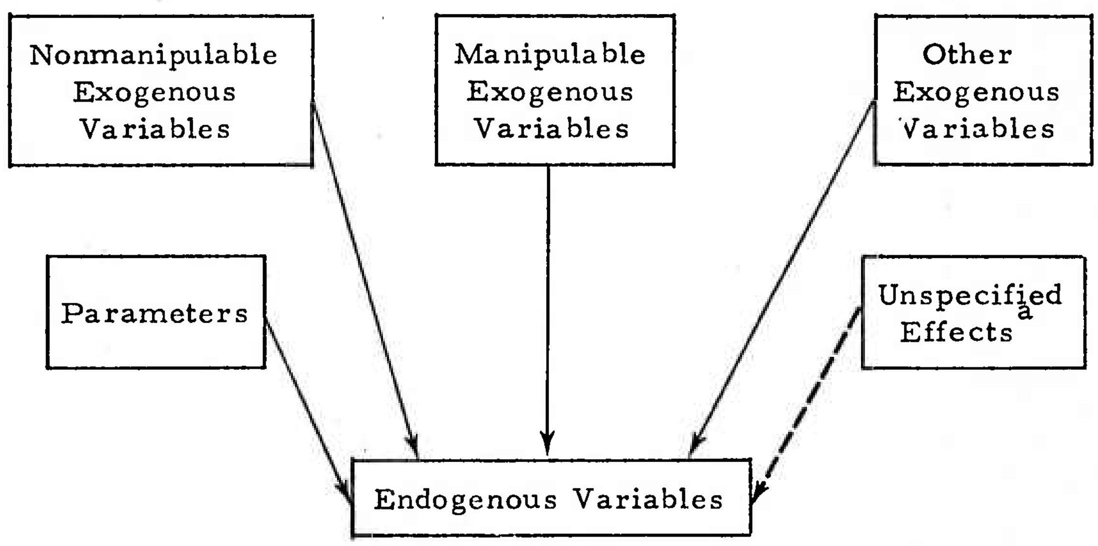
The values of endogenous variables are determined by other variables that can either be endogenous or exogenous. An example of an endogenous variable is the level of American-Canadian conflict in the above example.

Parameters. Parameters can be "conceptual" or "structural." A conceptual parameter is a factor that remains unchanged throughout the period examined. Consider, for example, a forecast of future Arab-Israeli areas of conflict. A conceptual parameter to this forecast is the continued presence of tensions between the parties. All

the data available on the relations between the Arab states and Israel refer to periods of conflict; thus there are no data for periods in which the relations were not hostile. Structural parameters, on the other hand, are parameters that are calculated by some empirical technique and are used directly in the forecast to tie variables together.

The relationship between parameters and variables is shown in Figure 1. Figure 1 indicates that various types of factors can affect values of endogenous variables. Endogenous variables are the

Figure 1. General Description of a Forecasting Model



[a] Unspecified effects are usually called "errors" or "residuals." These effects account for random noise, inaccuracies that arise from "left-out" variables, and inaccuracies that occur in linearizing a nonlinear relationship.

variables whose values are determined by the model. The figure demonstrates that the values of endogenous variables depend on the values of parameters and other variables. Thus the internal stability of a country may depend on its GNP per capita (a nonmanipulable exogenous variable), the level of government expenditures (a manipulable exogenous variable), the number of different racial groups in the country (a conceptual parameter), and the derived number of protests per dollar of government expenditure (a structural parameter).

By using Figure 1, a preliminary forecasting model can be generated. For this task to be successful, the analyst must first identify the objectives of his forecast. This will usually involve determining the appropriate time frame for the forecast. If the analyst is an expert in the area, he can pick those factors that will bring about his objectives, separate the factors into variables and parameters, and distinguish between endogenous and exogenous variables. In this manner, he can build a conceptual model which is then used to generate the forecast. Thus an international relations specialist in the State Department working at the Indian Desk who is required to forecast future Indian foreign policy should possess the expertise to choose relevant factors for the forecast. Often, however, the national security analyst may lack the required training for this task. In these cases, he will require help in selecting the appropriate factors that are necessary to build the forecasting model.

A PROCEDURE TO IDENTIFY RELEVANT FACTORS IN A FORECASTING MODEL

There are various ways whereby expert judgment can be employed to identify the important factors of a forecasting model. Of particular importance are Consensus Methods.

Consensus Methods.[1] There are two techniques within the general category of Consensus Methods that are particularly applicable in identifying the relevant factors of a forecasting model. They are the Committee Approach and the Delphi Technique.

> Committee Approach. This procedure involves relying on the opinion of experts. The output of this exercise is a list of factors that bring about the objectives of the forecaster. The Committee Approach is essentially a nonstructured way to arrive at the list.
>
> Delphi Technique. This method, somewhat more systematic than the above, involves four steps to produce a list of required factors.
>
> - Have a panel of experts list factors that bring about objectives.
> - Compile a master list with each factor accompanied by the number of times it is mentioned.
> - Submit the new list to the experts and request revisions.
> - Repeat the first two steps until the list no longer changes.

When the list of factors is obtained, the analyst must then determine which factors are variables and which are parameters in the time frame to be examined. To accomplish this, it may again be necessary for the analyst to employ some form of Consensus Methods, particularly if he is not an expert in the area of the forecast.

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1 For an explanation of Consensus Methods, see A General Handbook for Long-Range Environmental Forecasting, Vol. I (Arlington, VA, February 1973), pp. 18-24.

Once the factors relevant to the analyst's forecasting objective have been chosen, the forecaster must determine the assumed causal relationships among them.[2] It is important to note that the relationships considered are those presumed to exist on the basis of the expertise of either the analyst or his consultants. The estimation phase of the research may show that certain causal relationships initially deemed important by the experts are in fact nonexistent.[3] For example, international relations experts may believe that alignment between two nations is mainly affected by foreign aid received by one nation from the other. If this is not borne out by empirical examination, that hypothesis is rejected.

Relationships between variables fall into two general classes. First are those that relate variables in a rigorous and consistent manner, such as the trajectory of a particle in physics. These relations are termed "laws." Second are relations that are not consistently stable. In socio-political, military, and economic long-range forecasting, laws are extremely rare if not totally absent. Thus empirical estimation is required to discover the nature of relations in particular socio-economic and political systems. To accomplish this task systematically, the estimation must be structured. A modified use of Cross-Impact Matrices can be employed to discover whether the relations

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2 Causal relationships are characterized by cause and effect. Thus it may be that the alignment of Ecuador with the United States depends on the level of U.S. aid to that country--the larger the aid (the cause), the more the alignment (the effect).

3 Estimation involves calculating the values of structural parameters from sample data. This procedure is discussed in more detail in Chapter 3.

between variables are positive, negative, or absent, and to indicate which variables are endogenous and which are exogenous.[4]

The use of Cross-Impact Matrices in this context is illustrated in Table 1 by an example that contains three variables--A, B, and C. The forecaster is initially interested in knowing which variables bring about changes in other variables, that is, which variables are endogenous and which are exogenous. This causality can be determined by constructing and examining the following matrix.

TABLE 1

A PROCEDURE TO IDENTIFY CAUSALITY BETWEEN VARIABLES

Cause Variables	Effect Variables		
	A	B	C
A	0	X	0
B	0	0	X
C	0	X	0

If the forecaster or expert believes that a variable may cause a change in the value of another variable, the relationship can be indicated by a mark placed in the appropriate box. In Table 1, variable A causes changes in B, B causes changes in C, and C causes changes in B. If A represents the similarity in the ethnic background of the population of

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4 For a discussion of Cross-Impact Matrices, see the Handbook, pp. 33-39.

two countries, B represents their degree of alignment, and C represents the number of visits by their heads of state, then ethnic similarity affects alignment, alignment affects the number of visits, and the number of visits affects alignment.

A zero in a cell of the matrix indicates that there is no relationship from one variable to the other. If a column is composed only of zeros, then the corresponding variable is not affected by any other variables in the system and is, by definition, exogenous. If a column has at least one nonzero entry, then the variable is endogenous since its value is determined by at least one other variable. In the aforementioned example, variable A is exogenous since the first column is composed only of zeros. B and C, on the other hand, are endogenous variables since B is affected by A and by C, and C is affected by B.[5]

For forecasting purposes, awareness of the presence of causality between variables is necessary but not sufficient since the relationship between two or more variables can be positive, negative, or a combination of both.[6] This can be indicated by replacing the "X" mark with a "+" or "-" sign. In the previous example one would expect all

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[5] A close examination of Table 1 reveals that only the direct effects of a variable on another variable are measured. There are, nevertheless, indirect effects that are not mentioned in this case to keep the exposition simple. Thus variable A affects B, and B affects C; therefore A indirectly affects C. This, however, is not shown in the matrix. See John G. Kemeny, _et al._, _Introduction to Finite Mathematics_ (Englewood Cliffs, N.J.: Prentice-Hall, 1957), pp. 307-320 for further examples of the use of such matrices.

[6] A positive relationship between two variables implies that if the causal variable increases, then the effect variable also increases; the converse also holds. A negative relationship means that if the cause variable increases, then the effect variable decreases.

the signs to be positive since increases in ethnic similarity (A) tend to increase alignment (B), which in turn increases the number of visits (C), which further increases alignment. If, however, variable C represents the number of territorial disputes, the cell signs might be as follows:

TABLE 2

A PROCEDURE TO IDENTIFY THE SIGNS OF THE RELATIONSHIPS BETWEEN VARIABLES

Cause Variables	Effect Variables		
	A	B	C
A	0	+	0
B	0	0	-
C	0	-	0

Sometimes a cell has both a positive and negative sign in it, suggesting that one variable influences another variable in both a positive and negative fashion. This case is discussed in detail in the forthcoming section which examines some basic types of relationships.

The aforementioned steps of the forecasting procedure may at this point be illustrated by an example. Consider the following problem which involves forecasting the national power base[7] of Ghana in the

[7] We define national power base as the material and human resources available to a nation to influence its political environment.

year 1985. As described in the previous sections of the Guide, the forecast should proceed with the following steps:

1. Identify Factors

   a. Separate factors into variables and parameters.

   b. Separate variables into endogenous and exogenous variables.

2. Identify the signs (positive, negative, or zero) of the relationships among the factors.

Next, a Delphi panel composed of international relations experts familiar with the latest literature on all aspects of national power base is formed. Members of this panel should be experts on Ghana--its government, economy, foreign policy, military. The experts then carry out a Delphi exercise. The output of the exercise might be a list of factors such as that shown below:

- Military Factors

  --Number of men in armed forces

  --Defense expenditures

- Economic Factors

  --Gross national product

- Other Factors

  --Land mass of Ghana

  --Population

  --Percentage of population under 20 years of age

The list of factors should include both variables (e.g., size of armed forces) and parameters (e.g., land mass of Ghana).

The list of variables is further broken down into endogenous and exogenous variables. For this task, a matrix such as the one in Table 3 is constructed. In this matrix, the following factors are variables: number of men in the armed forces (A), defense expenditures (B), GNP (C), and population (D). This represents a total of four variables which can be categorized in a 4-by-4 matrix as follows:

TABLE 3

A HYPOTHETICAL MATRIX TO FORECAST THE POWER BASE OF GHANA IN 1985

Cause Variables	Effect Variables			
	A	B	C	D
A	0	+ X	0	0
B	+ X	0	0	0
C	0	+ X	0	0
D	+ X	0	0	0

In each cell of the matrix the forecaster inserts a zero or an X, depending on whether he feels a particular variable influences another

variable. For example, an increase in gross national product (C) may lead to an increase in defense expenditures (B); but an increase in population (D) will not influence defense expenditures. Of the four variables considered in the matrix only two, population and GNP, are exogenous since only zeros can be found in the columns under the two variables.

The next step in the forecast process involves discovering the signs of the relationships between the variables. The assistance of experts may be necessary at this point to help the forecaster. On the basis of the theoretical literature of national power base, all the relationships are believed to be positive.

Types of Relationships

There are three ways to express relationships between variables--mathematically, diagrammatically, and verbally. Only the first is adequate for systematically forecasting any but the most simple system with any degree of reliability. Nevertheless, the other two methods are critical adjuncts to the process of building models. For expository purposes, the second method was selected to describe certain common types of relationships. First, the bivariate case (one with two variables) was chosen. Second, the multivariate case (one with more than two variables), in which an endogenous variable is related to more than one exogenous variable, is discussed.

The bivariate case can be illustrated diagrammatically since it requires only two dimensions (axes). Consider the following figures which describe a positive relationship between variables A and B.

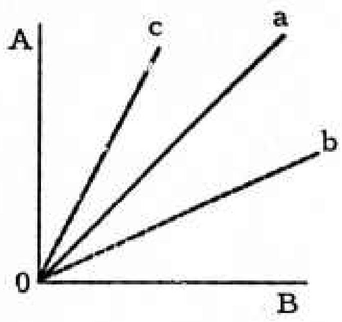

Figure 2

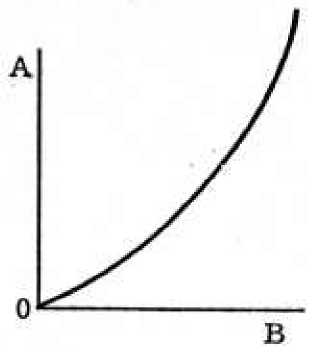

Figure 3

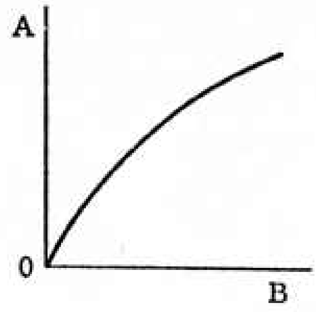

Figure 4

Examples of Positive Relationships

Furthermore, assume that causality exists between A and B in a manner that the occurrence of B causes the occurrence of A.[8] Alternatively, A is the endogenous variable while B is the exogenous variable. Considering the function 0a in Figure 2, an increase of 10 units in the value of B brings about an identical increase in the value of A (if both are measured in the same units). This is a linear relationship. It is possible, however, that another functional relationship such as 0b relates A to B. In this instance an increase in B brings about a smaller increase in A. On the other hand, if the function is located to the left of 0a (0c for example), an increase in B brings about a larger increase in A.

Unlike Figure 2, the nature of the relationship between A and B in Figure 3 is nonlinear. This absence of linearity implies that the impact of B on A is not constant throughout the curve but changes

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8 In this discussion we are only considering static analysis (A causes B instantaneously with no time lag). In dynamic analysis, however, a change in B may cause a change in A after a time lag.

according to the magnitude of B. Incremental increases in B cause more than proportional incremental increases in A. This type of relationship is called an exponential relationship and is sometimes used by demographers to illustrate population growth. Figure 4 describes a logarithmic relationship. In this case, successive increases in B bring about smaller and smaller increases in A.

The functional relationships portrayed in Figures 2, 3, and 4 described positive relationships between variables A and B. Negative relationships between variables may exist as shown in Figures 5-7.

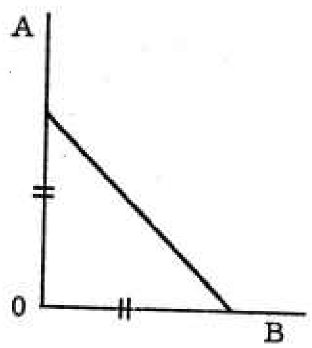

Figure 5

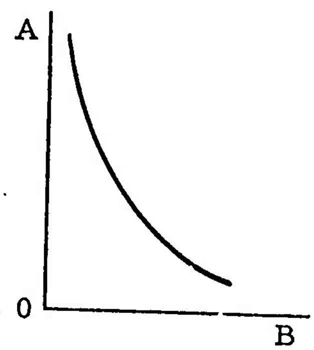

Figure 6

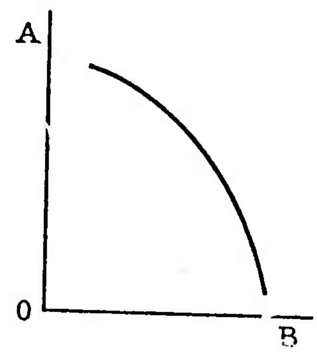

Figure 7

Examples of Negative Relationships

Figure 5 presents an inverse linear relationship between A and B which is similar to the relationship portrayed in Figure 2; but it is negative since an increase in B brings about an identical decrease in A. In Figures 6 and 7 the functional forms are such that an increase in B brings about decreases in A at a decreasing rate in the first instance and at an increasing rate in the second.

In both sets of figures, the relationships were portrayed in a manner such that the endogenous variable either increased or decreased for all values of the exogenous variable. It is possible, however, for a relationship to increase the value of the endogenous variable for some values of the exogenous variable, and to decrease the value for other values of the exogenous variable. This is what is meant by both positive and negative signs in the cells of the matrix in Table 2.

Examples of these types of relationships are given in Figures 8 through 10.

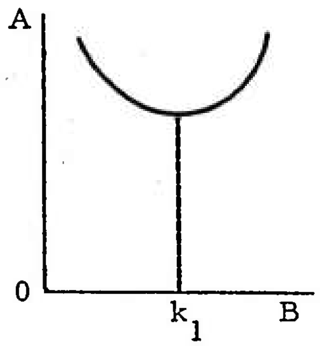

Figure 8

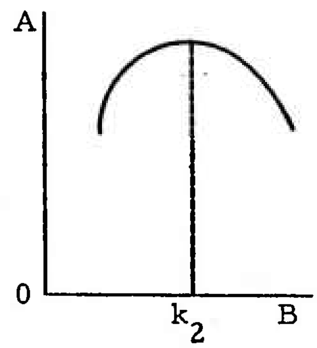

Figure 9

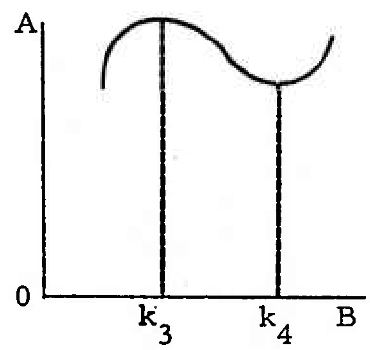

Figure 10

Examples of Higher Order Relationships

Figures 8 and 9 portray "quadratic" relationships, while Figure 10 portrays a "cubic" relationship. In Figure 8, any increase in B to the left of k_1 brings about a decrease in A; any increase in B to the right of k_1, however, brings about an increase in A. The opposite relationship holds in Figure 9. Finally, in Figure 10, both characteristics of Figures 8 and 9 hold depending on which values of B are chosen.

Every relationship described thus far considered only two variables. In the real world, however, relationships are often multivariate, that is, values of the endogenous variable are not determined by a single exogenous variable but by two, three, or more exogenous variables. Thus the alignment of Sri Lanka (Ceylon) with respect to the United States may depend on 1) the number of visits by heads of state between the two countries, 2) the level of United States aid to Sri Lanka, and 3) trade patterns between the two countries. To describe these variables diagrammatically is difficult since only two-dimensional relationships can be realistically portrayed graphically. Relationships among three variables can be expressed in the form of "three-dimensional solids." Relationships among more than three variables cannot be conceived (at least by most people) since we are constrained by the three-dimensional world we live in. An attempt is made in Figure 11 to draw a three-dimensional diagram expressing the relationships among three variables in two-dimensional space. Variable A is the endogenous variable, while B and C are the exogenous variables. The function relating the three variables is not a line (such as in the previous figures) but a two-dimensional plane or surface (w x y z). A point on the plane, such as M, will have three coordinates--a, b, c--one coordinate for each axis.

In this chapter important basic types of relationships were presented. In mathematics there are an infinite number of such relationships that may relate variables to each other. In the social sciences we concentrate on relatively simple forms. Yet to establish these forms empirically, data on the variables are necessary. This is the topic of the next chapter of this Research Guide.

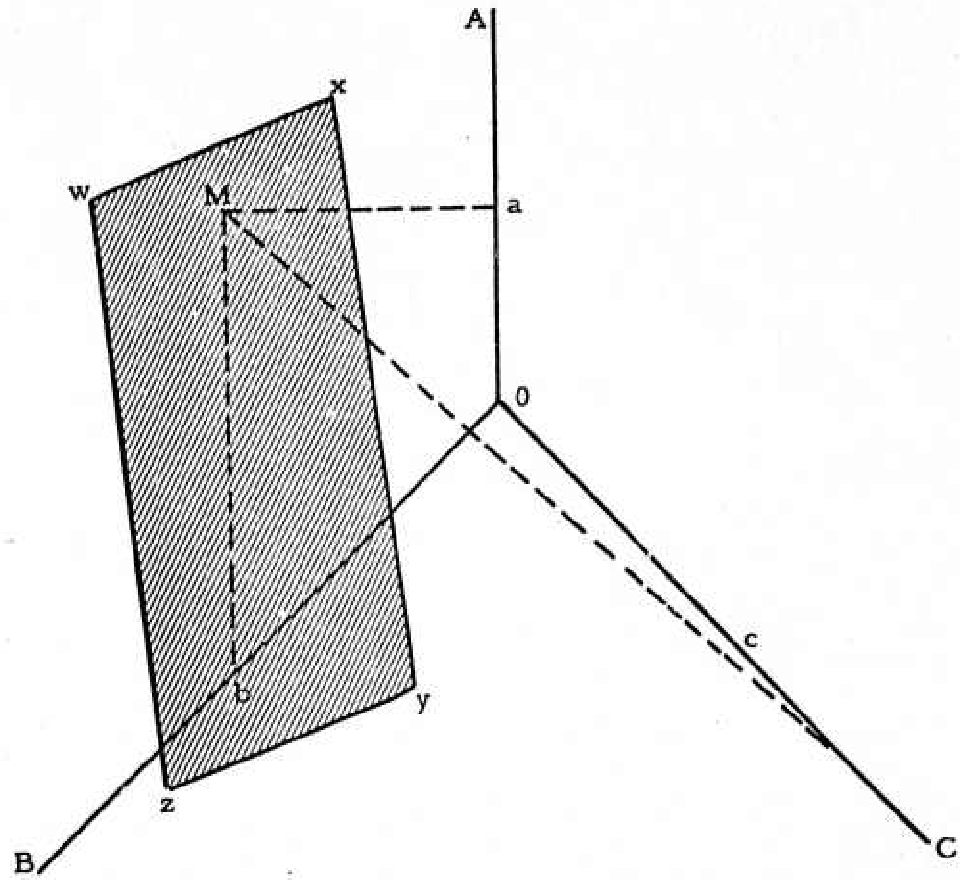

Figure 11. Example of a Multivariate Relationship

CHAPTER 2: DATA COLLECTION

There are three distinct but related problems in the data collection phase of a forecasting effort:

- Selecting indicators of the variables
- Operationalizing the variables
- Collecting the data

Selecting the indicators of a variable involves discovering those directly measurable variables that best "tap" the meaning of a conceptual variable. Operationalizing a variable involves determining precisely how the indicators are to be measured and combined. Collecting the data is simply performing the actual measurements.

THE CHOICE OF INDICATORS

In the previous chapter, the determination of the forecasting model was made on the basis of conceptual variables. A conceptual variable is one that has direct meaning to the forecaster in a causal sense. The wealth or power of a nation and the level of conflict or alignment between or among nations are such variables. However, to perform a forecast with precise, unambiguous results, it is absolutely necessary to measure such conceptual variables in such a way as to provide an unimpeachable basis for the use of the forecast.

To do this one must often use indicators of conceptual variables. An indicator of a variable is usually some other variable that is used to

measure the original conceptual variable. For example, the GNP of a nation can be used as an indicator of that nation's economic power base. The voting patterns of nations in the United Nations may be an indicator of their alignment.

There is no systematic method to determine a priori the best indicators of a conceptual variable. Experts in the area are the most qualified persons to select these indicators since they are familiar with the latest theoretical and empirical research in the area. It is important to choose as many indicators of a variable as possible, and the expert may be in the best position to do this. Some variables may admit to relatively few possible indicators, such as economic power base, while others may have a large number of indicators, such as conflict between nations. In either case, however, it is important to be as thorough as possible in identifying indicators.

Obtaining the greatest possible number of indicators is important because the forecaster may find that some data are not available for particular indicators, and/or the indicators may be statistically related. In the first situation, the effect on the quality of the forecast is greatly reduced when inappropriate indicators must be used. In the second situation, there are somewhat more complex consequences. If the indicators of a conceptual variable are highly correlated, the variable may be homogeneous. If this is the case, then only one of the indicators is needed to measure the variable. If the indicators are not highly correlated among themselves, the variable is heterogeneous, and it will be necessary to combine values of these indicators to measure the variable. Whether a conceptual variable is homogeneous or heterogeneous will not usually be known when indicators are selected; therefore it is important to select as many indicators as possible.

OPERATIONALIZING THE VARIABLES (INDICATORS)

Operationalizing a variable means determining precisely how the individual indicators are to be measured and the most likely procedures for combining them to form variables. This phase clearly overlaps with the data collection phase in that certain operational distinctions must be made after the data are available; but a number of important decisions must be made prior to data collection.

The most fundamental decision that must be made is precisely how to measure the indicator. This decision will affect the remainder of the forecast process, since it prescribes the manner in which the data will be collected, and may preclude later revision of the data. For example, if military power base is the conceptual variable, and the military manpower of a nation is one indicator, it is crucial to determine precisely what is meant by military manpower. One would estimate the number of individuals in the army, navy, air force, and rocket force. But should the number of individuals in the coast guard, the ready reserves, and the militia be counted? Should one be prepared to accept the official government figures for these indicators, or should one standardize on some "impartial" source such as the International Institute for Strategic Studies? And does one want to attempt to "weight" such figures by estimated level of training, degree of readiness, and quality of leadership, or are these components of some other indicator? These questions must be asked prior to data collection.

After the data are collected, a single measure of the conceptual variable is created. The question of homogeneous or heterogeneous variables can be tested at this point. To continue the above example, if

one had arrived at an acceptable definition of military manpower and were able to collect the required data, one would need to know how to combine the data with other indicators of military power base. The values of the indicators could be correlated with each other, and the resulting pattern analyzed.

Every pair of indicators has a correlation coefficient that indicates how strongly the two indicators vary together. If all of the correlation coefficients are sufficiently high (a figure of $\pm$ 0.80 may be a useful cutoff) then the variable may be homogeneous, and any single indicator can be selected. If most of the indicators are highly correlated, it may be possible to ignore the ones that are not highly correlated and still select one indicator from the homogeneous group. If this is not possible (because an uncorrelated indicator is too important to omit) or if there is no pattern of homogeneity, then the variable must be heterogeneous, and the operationalization process continues by constructing an index of the variable that considers all of its indicators properly weighted. There are three ways to construct such an index. The first is judgmental and permits the expert to say that one indicator is two or three (or whatever) times as important as another indicator, and to weight all indicators by such a procedure. The second is quantitative and uses Regression Analysis[1] by which the forecaster creates values of the composite variable from expert judgment for a sample of cases, and then uses least squares to determine the weights for the indicators that best reproduce those values. The third is Factor Analysis[2] which is a powerful tool to derive

1 See the Handbook, pp. 46-52.

2 See R. J. Rummel "Understanding Factor Analysis," Journal of Conflict Resolution (December 1967), pp. 444-480.

weights determined entirely by the degree of correlation among the indicators themselves. In all three cases, the weights are then used to construct the values of the variable for use in the forecast-estimation phase.

DATA COLLECTION ON THE VARIABLES

Two potential problems that must be solved confront the analyst at this point in the research. They concern the reliability and availability of the data for any given indicator. Data quality is crucial for precise and reliable forecasts. There are three possible sources for most socio-economic and political data. The first source is the forecaster himself who creates the data and develops a coding procedure. Generally, data obtained by coding are subject to errors that arise when specifying certain coding rules (operationalization) and when applying those rules. Errors also occur when coding rules are changed in the middle of the data-gathering process, thus preventing data comparisons. This is especially acute in data collected at different times (time-series data) since the coding rules themselves may change. Errors in specifying the coding rules can be corrected by expertise. Errors in applying the coding rules can be controlled by applying constant checks on the coders' performance.[3]

A second and more important data source (to the international affairs forecaster) is governments or other official data collection agencies. In addition to previously mentioned errors, government data may contain biases that are either conscious or unconscious. Governments sometimes deliberately present biased data for political reasons.

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[3] For a detailed explanation of various coding procedures, see Kenneth Janda, Data Processing (Evanston, Ill., Northwestern University Press, 1969), Chapter 2.

More importantly, government data created as it is for other purposes is often nearly, but not exactly, what the analyst wants. The analyst must adjust biased government data whenever he detects a bias.

Another source of data is provided by such international organizations as the United Nations, OECD, and the World Bank. These agencies do not usually collect the data but report data collected by individual governments. These agencies do, nevertheless, attempt to categorize the data and make them comparable across countries. Moreover international organizations may correct the data when conscious biases are present.

Data availability is another important problem analysts must face in the data collection phase. A set of data is very seldom complete. This is especially true of political and social data as well as economic data. Generally speaking, quantitative techniques of forecasting require complete data sets, while qualitative techniques can be applied to incomplete sets of data. If the analyst wants to employ quantitative techniques, he must fill in the gaps in the data. There are various ways to create "missing" data. Some of the important methods are discussed as follows:[4]

> <u>Fragmentary evidence and "expert" judgment:</u> Informed opinion and verbal descriptions can be used to obtain estimates of missing data. Though obviously subject to bias, this method may be useful where there is considerable prior knowledge about a particular case.

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[4] J. Odell, "Approaches to the Missing Data Problems" (unpublished paper, University of Wisconsin, October 1972).

Use of mean, mode, or median.[5] One of the most common methods for handling missing data is to substitute their mean value. Means are computed by using all cases having data on the variable. Depending upon specific characteristics of the variable in question, the mode or median may be preferred over the mean. This method relies solely upon available data and thus avoids judgmental bias. However, averages tend to underestimate the total amount of variance from the mean, that is, the number of extreme values is reduced. Estimates using means, medians, or modes are most appropriate where available data cluster around one of these values.

Rating by distribution of available cases: This approach combines both judgmental and empirical information. For a variable with missing data, the mean value is computed using all cases on which data are available. Additional data points are obtained by determining judgmentally the number of standard deviations the new data are from the mean. Rating is an improvement over simple reliance upon the mean when the researcher has some prior knowledge about a variable's distribution.[6]

Once the missing data have been derived, the levels of measurement of the indicators and those used as predictors must be identified if the analyst is to proceed with the operationalization phase of the forecast.[7] If quantitative techniques of estimation are to be used, the level of measurement of the available data determines the appropriateness of the technique.

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5 This technique to manufacture data is not appropriate for time-series data. For example, missing data on GNP cannot be substituted by mean values of the data set since GNP usually increases with time.

6 A description of the various levels of measurement that socio-economic and political data can assume is found in the Handbook, pp. 11-13.

7 Regression analysis is also sometimes used to generate missing data. For an explanation of this technique, see the Handbook, pp. 46-52.

CHAPTER 3: PARAMETER ESTIMATION

By the time the analyst reaches this step in the forecasting process, he should have developed a conceptual model in which every variable has been operationalized and classified as endogenous or exogenous. Moreover, the analyst should have familiarized himself with the basic types of relations and identified and collected various data that describe the variables.[1] If the data and the model "fit" each other, that is, if there is no discontinuity in the data, then the estimation procedure phase can be initiated. If there are gaps in the data, however, they must be filled by implementing some of the techniques described earlier.

There is a second problem that may prevent the model and the data from fitting each other. This problem is related to the presence of different types of data categories. Data can be nominal, ordinal, ratio, or interval.[2] In certain instances it may be impossible to employ certain estimation techniques if the level of measurement is low (nominal or ordinal). Input-Output Analysis, for example, is a technique that requires interval data. If the data available are only of the nominal category, then the aforementioned technique cannot be employed. This problem can impose certain constraints on the parameter estimation phase of the forecast effort.

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[1] An in-depth knowledge of the various types of relationships discussed in Chapter 1 is not absolutely necessary for the forecast process; it is, nevertheless, helpful.

[2] For an explanation and discussion of the difference between the categories, see the Handbook, pp. 11-13.

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[2] For an explanation and discussion of the difference between the categories, see the <u>Handbook</u>, pp. 11-13.

Estimation is the process of obtaining values of the structural parameters of the model that express the relationships and the manner by which variables are related to each other. Since the parameter values are estimated from past data, the relationships among the variables are valid for the past. The forecast process assumes that these functional forms will also hold in the future.[3]

The procedures for estimating parameter values are categorized in Table 4. The forecaster should select an estimation technique from among those listed in the table.

TABLE 4

THE CHOICE OF ESTIMATION TECHNIQUES

Parameter Type	Estimation Technique	
	Judgmental	Empirical
Conceptual	Experts	Data Examination
Structural	Delphi Cross-Impact	Regression Analysis Input-Output Analysis Game Theory Models etc.

3 It is crucial to note that in any forecasting process, the data and analyses are based on the past. Quantitative techniques merely make this dependence explicit, whereas qualitative techniques may permit the dependence to be hidden.

As was stated earlier, it is important to distinguish between conceptual and structural parameters. A conceptual parameter is a factor that remains unchanged throughout the period examined and is not included explicitly in the model. Structural parameters, on the other hand, are parameters that are calculated via some empirical technique and are directly used in the forecast. Upon examining the factors, it may become apparent that some parameters are conceptual parameters, such as the pressure of conflict between Israel and the Arab states referred to in Chapter 1. Forecasts based on conceptual parameters will produce inaccuracies. Because of the possibility of these biases, it is very important to examine the data carefully to discover if conceptual parameters are indeed present. In cases where there are no data, or where the level of measurement in the data is low, judgmental expertise must be used to determine whether conceptual parameters are present in the system forecast. If conceptual parameters are part of the data, the estimates are valid given the presence of those parameters.

A PROCEDURE TO CHOOSE ESTIMATION TECHNIQUES

The analyst should attempt to use estimation techniques located in the lower right-hand portion of Table 4. Yet there are many constraints that may prevent him from doing this. First, the functional forms that relate the variables to one another may not be known, rendering any empirical estimation difficult. Second, the level of measurement of the data can impose difficulties on the use of certain quantitative estimation procedures. Third, quantitative techniques cannot be used when there are fewer cases than structural parameters to be estimated. This is a problem so serious as to prevent almost any kind of

systematic estimation. It can, however, be solved by acquiring additional cases.[4]

Despite the presence of these constraints, every effort should be made by the analyst to choose quantitative techniques of estimation. This choice is recommended not because the authors have a blind commitment to quantitative methods but because quantitative techniques of estimation will give rise to more precise, explicit, accurate, and hence reliable forecasts. Quantitative methods are superior to qualitative techniques for three principal reasons. First, they require that definitions of variables be exact and that assumptions be stated explicitly. Second, quantitative estimation can consider complex relationships among variables that cannot be evaluated verbally. Third, quantitative techniques reduce biases that are introduced into the forecasts by value judgments and the limited memories of analysts. The most popular technique for parameter estimation is Regression Analysis.[5] Nevertheless, there are other available techniques such as Input-Output Analysis and Game Theory Models.[6] In the absence of appropriate data, the forecaster may use a judgmental estimation technique such as Delphi.[7]

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[4] This is a mathematical problem that requires that the number of unknowns should be less than or equal to the number of equations.

[5] For a discussion of Regression Analysis, see the <u>Handbook</u>, pp. 46-52.

[6] <u>Ibid.</u>, pp. 57-60 and pp. 73-79 respectively.

[7] <u>Ibid.</u>, pp. 18-24.

THE PROBLEM OF FORECASTING EXOGENOUS VARIABLES

Once the parameters of the forecasting model have been estimated, the forecaster has a model that relates variables to each other. These relationships have been derived on the basis of past data on the variables. The model relates every endogenous variable to exogenous variables and parameters. The forecasting problem involves projecting the data beyond the confines of the past. This requires forecasting values of the exogenous variables that are then combined with the parameters to yield future values of the endogenous variables.

Ideally, exogenous variables should be manipulable. If planners could set the values of the exogenous variables in the same manner that the Federal Reserve System fixes the supply of money in the U.S. economy, then planners could help bring about the future environment they consider most desirable. In long-range environmental forecasting, however, this second characteristic is often lacking and planners cannot influence future outcomes. If the exogenous variables of the forecasting model are not manipulable variables, then they must be predicted.

On the surface it appears that there are two ways to forecast exogenous variables--quantitatively or judgmentally. Realistically, however, only the latter procedure is available. Let us illustrate each of these procedures by an example. If, on the basis of past data, the domestic stability of India is found to be dependent on its GNP per capita, then the future domestic stability may be forecast by first estimating future Indian GNP per capita. To generate this latter forecast, one may use an econometric model. Nevertheless, this approach does not solve the problem since the exogenous variables

of GNP per capita remain to be forecast. In fact, the domestic stability and the econometric models can be incorporated into one in which the exogenous variables of GNP per capita are used to forecast stability.

Since the use of another model to generate forecast values of predictor variables does not really solve the problem but postpones it, the variables have to be forecast by using a qualitative technique. The General Handbook contains a detailed description of important techniques that may be used in this context. Some of the important techniques are Consensus Methods, Scenarios, Morphological Analysis, and Cross-Impact Matrices. The forecast of the endogenous variables can proceed by combining future values of the exogenous variables with the structural parameters of the model.

This general approach which forecasts exogenous variables qualitatively implicitly assumes that these variables are easier to forecast qualitatively than endogenous variables. If this assumption is not made, then one could ask why not treat all variables exogenously and forecast them using some qualitative technique? Alternatively, why build quantitative models altogether? A totally qualitative methodology appears less cumbersome than one which first derives a model which requires quantitative estimation of the parameters of the model and then qualitative estimation of future values of its predictor variables. There are two reasons for this approach to long-range forecasting. First, certain variables are easier to predict than others, and hence forecasts would be more accurate if the endogenous variables are first expressed as quantitative functions of exogenous variables which may be easier to forecast. Second, a quantitative model can account for many functional relationships which are not readily apparent. It is for these reasons that this two-step approach to forecasting is suggested.

CHAPTER 4: A SIMPLE FORECASTING MODEL

Let us assume that a national security analyst is interested in forecasting the national power base of the People's Republic of China in the 1985-1990 period. Furthermore, suppose the analyst lacks professional training in the areas of political science and international relations. The question that arises is how does he generate such a forecast. This chapter will develop a step-by-step procedure to forecast the national power base of the People's Republic of China over the long range.

There are four basic steps to this procedure:

- Building a conceptual model
- Collecting the data
- Estimating the parameters
- Generating the forecast

BUILDING A CONCEPTUAL MODEL

To build a conceptual model, the analyst must compile a list of factors that can be used to forecast the national power base of the PRC in the 1985-1990 period. The list should include both variables and parameters. To put the list together, the analyst should contact established China experts who are also interested in the concept national power base. Consensus Methods can be employed to generate such a list. A hypothetical list of factors is presented in Table 5. This list is presumed to have been drawn up after considerable interaction

among the experts either through the use of the Committee Approach or the Delphi Method.

TABLE 5

HYPOTHETICAL LIST OF FACTORS USED TO FORECAST THE NATIONAL POWER BASE OF THE PRC

Parameters	Variables
GNP Growth Rate	Economic Power
Net Population Growth Rate	Military Power
Geographical Area of Country	Total Population
Number of Ethnic Groups in Country	Energy Consumption
Capital Accumulation Rate	Estimated National Resource Endowment
	Proportion of GNP Generated by Foreign Sector
	Gross Steel Output
	Length of Highway Network

The separation of variables into endogenous and exogenous variables can be accomplished by using a modified Cross-Impact Matrix. This procedure involves three steps:

- Make up a matrix of all variables.
- Measure effect variables on the columns of the matrix and cause variables on the rows of the matrix.
- Classify all variables with zeros in columns as exogenous.

The variables of Table 5 are labeled X_1 through X_8 in Table 6 as follows:

TABLE 6

LABELING OF VARIABLES

Variable	Name of Variable
X_1	Economic power
X_2	Military power
X_3	Total population
X_4	Energy consumption
X_5	Estimated national resource endowment
X_6	Proportion of GNP generated by foreign sector
X_7	Gross steel output
X_8	Length of highway network

These eight variables will yield an 8 by 8 matrix as shown in Table 7. The analyst places checks in those cells where he feels causality exists between any two variables. Thus if X_1 is believed to cause a change in X_2, a check is place in the appropriate cell in Table 7. Causality is presumed to exist either on the basis of past empirical research or on theoretical premises. This presumes that the analyst is acquainted with empirical studies and with political science and international relations theory. If the analyst does not possess such expertise, then he must rely on help from the panel of experts. In the example considered, the following variables are exogenous: population, proportion

of GNP generated by the foreign sector, gross steel output, and length of the highway network. This implies that the national power base of the PRC will be forecast from the four aforementioned exogenous variables.

TABLE 7

SEPARATION OF ENDOGENOUS FROM EXOGENOUS VARIABLES[a]

Cause Variables	Effect Variables							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	0	X	0	X	X	0	0	0
X_2	X	0	0	X	X	0	0	0
X_3	X	X	0	X	X	0	0	0
X_4	X	0	0	0	0	0	0	0
X_5	X	X	0	X	0	0	0	0
X_6	X	X	0	0	0	0	0	0
X_7	X	X	0	X	X	0	0	0
X_8	X	X	0	X	0	0	0	0

[a] Only direct effects are measured in the matrix.

The next step in the forecast process is to identify the sign of the various relationships among the variables. To accomplish this, we examine the matrix and place a positive or negative sign in those cells that have been marked with an X. Decisions as to whether the relationship between two variables is positive or negative are made either on the basis of theoretical principles or on the observation of past empirical studies that have identified such relationships. By recalling the matrix, the following signs are inserted in each cell:

TABLE 8

IDENTIFICATION OF THE SIGNS OF RELATIONS

Cause Variables	Effect Variables							
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
X_1	0	+	0	+	-	0	0	0
X_2	-	0	0	+	-	0	0	0
X_3	-	+	0	+	-	0	0	0
X_4	+	0	0	0	0	0	0	0
X_5	+	+	0	-	0	0	0	0
X_6	-	-	0	0	0	0	0	0
X_7	+	+	0	-	-	0	0	0
X_8	+	+	0	+	0	0	0	0

COLLECTING THE DATA

The next step in the forecast process is to collect the data on the variables. Under this phase of the forecast effort, the analyst must perform three tasks:

- Choose indicators on the variables.
- Operationalize the variables.
- Collect data on the variables or indicators.

Let us examine each of these tasks individually. The national power base of the PRC is assumed to possess an economic dimension and a military dimension. In order to derive an overall operational measure of national power base, proper weights for each dimension are derived. In this manner, national power base can be expressed as:

$$a_1 \text{ (economic power)} + a_2 \text{ (military power)}$$

where a_1 and a_2 are judgmentally determined weights.

To obtain indicators of each component of national power, the analyst should once again consult the experts. Possible indicators of each dimension are listed in Table 9. The operationalization proceeds by specifying precisely how the indicators are to be measured. Another step in this phase of the forecast effort involves gathering data on the indicators. The various sources of data and problems encountered in data collection have been fairly well discussed[1] and there is no point in repeating them here.

---

[1] See Chapter 2 of this Guide. To obtain data on the aforementioned indicators the analyst may consult the Handbook, Vol II.

TABLE 9

LIST OF INDICATORS OF ECONOMIC AND MILITARY POWER

Economic Power	Military Power
GNP	Manpower in armed forces
GNP per capita	Nuclear capability
Percent of GNP generated by industrial sector	Defense budget
	Quantity of hardware

When data on the indicators have been chosen, the analyst must discover whether economic and military power are homogeneous or heterogeneous variables. If they are homogeneous, then one indicator for each variable would be sufficient to represent the variable. To determine these characteristics of the indicators, the correlation coefficients for each pair of variables must be calculated either by using a simple "canned" computer program or an electronic desk calculator. For the purposes of this example, it will be assumed that the values of the coefficients are close to one, and thus one indicator for economic power and one for military power would be sufficient to represent those two variables. The indicators picked are GNP and size of defense budget, respectively. The national power base (NPB) of the PRC is now operationalized as follows:

$$\text{NPB} = a_1 \text{ (GNP)} + a_2 \text{ (defense budget)}.$$

The national power base model can be expressed as:

> ... a function of total population (X_3), energy consumption (X_4), estimated national resource endowment (X_5),

proportion of GNP generated by the foreign sector (X_6), gross steel output (X_7), and length of highway network (X_8).

Of the aforementioned variables, X_4 and X_5 are endogenous. This means that these variables are determined by the exogenous variables of the forecast model. Symbolically, the forecast equation for national power base is written as:

$$NPB = A_0 + A_1X_3 + A_2X_6 + A_3X_7 + A_4X_8 + e$$

where e represents unspecified effects.[2]

ESTIMATING THE PARAMETERS

The forecast effort at this point involves estimating values of A_0, A_1, A_2, A_3, and A_4 using past values of the variables (NPB, X_3, X_6, X_7, and X_8) and one of the techniques described in the Guide.[3] Since ratio-level data are available for all the variables of the model, Regression Analysis can be used to estimate the values of the parameters. A hypothetical estimated equation is:

$$(1)\quad NPB = 1280.21 + 140.89X_3 + 125.19X_6 + 220.18X_7 + 9494.12X_8 + e$$

---

2 e represents unspecified effects, i.e., errors that are introduced into the equation from three possible sources--random noise in the data, omitted variables, and errors that occur when linearizing a nonlinear relationship.

3 See Chapter 3 of the Guide.

This equation is in fact the forecasting model.[4] To obtain future values of the national power base of the PRC, future values of X_3, X_6, X_7, and X_8 are substituted into the equation. Thus, if the analyst wants to forecast the value of the PRC's national power base in 1990, he multiplies X_3 (the population of the PRC in 1990) by 140.89 and adds it to the percentage of GNP generated by the foreign sector in 1990 multiplied by 125.19. This in turn is done for the other two variables--gross steel output in 1990 and length of highway network in 1990. Finally, 1280.21 is added to the total sum. This procedure first requires estimating the values of X_3, X_6, X_7, and X_8 in 1990.[5]

GENERATING THE FORECAST

To generate the forecast, Consensus Methods are used to forecast the values of the exogenous variables for the 1985-1990 period. Table 10 presents the forecast values for population, percentage of GNP generated by the foreign sector, gross steel output, and length of highway network.

Forecast values of the exogenous variables are now plugged into equation (1) to yield the national power base of the PRC in the 1985-1990 period. The forecast is presented in Table 11.

---

4 We are assuming that this equation has been estimated with data that cover the 1950-1970 period.

5 This estimation was discussed under the heading of "The Problem of Forecasting Exogenous Variables" in the Guide, pp. 31-32.

TABLE 10

JUDGMENTALLY DETERMINED
FORECAST OF THE EXOGENOUS VARIABLES

Year	Variables			
	X_3^a	X_6^b	X_7^c	X_8^d
1985	912	8.5	151	158
1986	930	8.3	166	162
1987	946	8.9	181	167
1988	965	9.1	196	169
1989	983	9.5	215	171
1990	998	10.2	232	173

[a] in millions of people

[b] in percent

[c] in millions of tons

[d] in thousands of miles

TABLE 11

FORECAST VALUES OF THE
NATIONAL POWER BASE OF THE PRC (1985-1990)

Year	National Power Base[a]
1985	163
1986	170
1987	175
1988	180
1989	187
1990	194

[a] in billions of 1970 dollars

EVALUATING THE FORECAST

There is no a priori method whereby the analyst can check the accuracy of his forecast. He can, however, utilize a procedure known as postdiction, that is, evaluating the accuracy of his estimates by recalculating past values of the national power base of the PRC using the model and comparing these values to real values. There are two types of postdiction that can be undertaken. The first involves using the estimated values of the parameters and intercept to recreate the national power base of the PRC over past periods (Postdiction Type I). The second way to evaluate the accuracy of the estimates involves using a subset of the data to calculate estimates of the parameters and intercept of the national power base equation and compare predicted versus actual values for another subset of the data. Let us concentrate on each type of postdiction individually.

In the aforementioned forecast example, it was assumed that the parameters of the national power base equation were estimated by using 1950-1970 data on national power base, population, percent of GNP generated by the foreign sector, gross steel output, and length of the highway network. The first way the model can be evaluated is to use these parameters to reestimate the values of national power base in the 1950-1970 period. In this manner estimated national power base can be compared to actual national power base. A hypothetical comparison is presented in Figure 12.

A second way to evaluate the model is to use a subset of data (e.g., data for 1950-1960) to generate another subset of data (e.g., predictions for the 1960-1970 period). A hypothetical comparison of this type of test is presented in Figure 13. From the figure, it can be

noticed that the error between the actual and predictor value of national power base is higher than in Postdiction Type I. This is to be expected since the former parameters are estimated from a large data sample--1950-1970 versus 1960-1970. Thus the larger the data sample, the more precise will be the estimates.

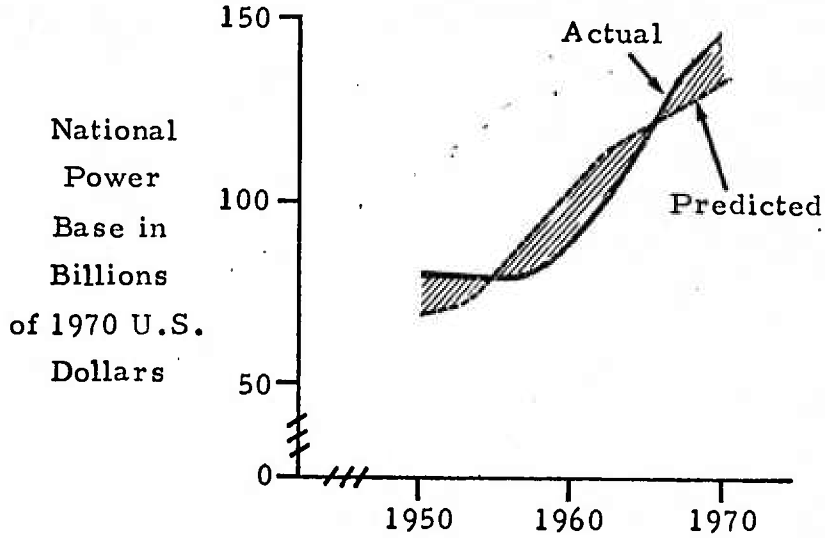

Figure 12. Postdiction Type I.

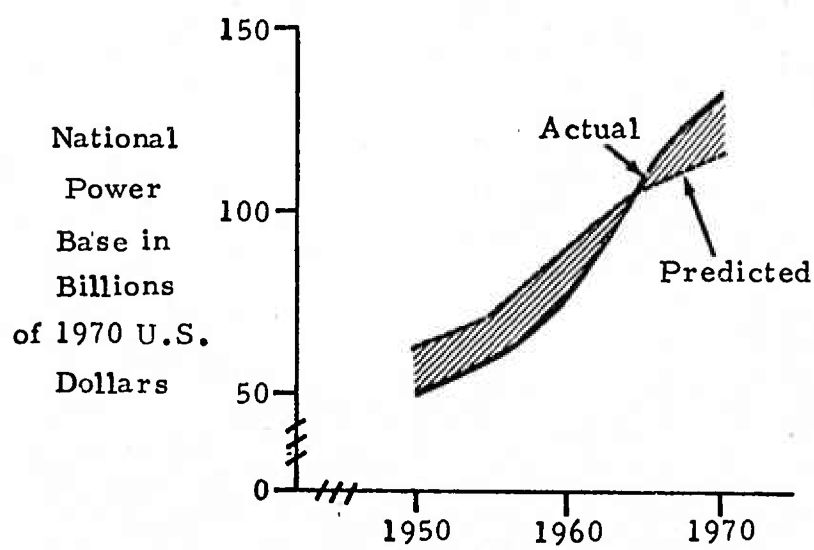

Figure 13. Postdiction Type II.

CONCLUSION

In this Guide, we have developed a procedure for empirical research in long-range environmental forecasting. The Research Guide will be useful to analysts who are familiar with the material included in CACI's General Handbook referred to earlier. Many of the estimation procedures presented in the Guide require the use of computers since they involve extensive arithmetic manipulations. Thus the analyst or his associates should be familiar with the basic operations of a computer or a terminal tied to a computer. No knowledge of programming is required since most of the programs that would be required are found in canned form in computer libraries.

To obtain reliable and precise long-range forecasts of the international environment, three equally important items are required--techniques of forecasting, theory and knowledge, and data. Techniques of forecasting are by and large readily available. They have been developed by mathematicians, statisticians, and economists. For the most part, the analyst is faced only with identifying the techniques that are appropriate to his needs. To help the analyst in this task, CACI has prepared Volume I of the Handbook which describes 11 important forecasting techniques. Many national security analysts, however, are not fully acquainted with international relations theory. To overcome this drawback, the use of experts has been suggested. Finally, reliable and precise forecasts of the international environment require data. To assist defense analysts in this area, CACI has prepared Volume II of the Handbook which describes 300 data files containing over 7,000 variables.

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13. ABSTRACT

The overall purpose of this Interim Technical Report is to provide the basis for the improvement of long-range environmental forecasting through the use of quantitative methods. This volume provides a step by step procedure that analysts can use to generate forecasts of the long-range environment. The document is based on and should be used in conjunction with CACI's A General Handbook for Long-Range Environmental Forecasting, Interim Technical Report No. 2 (February 1973).

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